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Constructing Scientific Arguments Using Evidence from Dynamic Computational Climate Models

Amy Pallant · Hee-Sun Lee

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Abstract Modeling and argumentation are two important scientific practices students need to develop throughout school years. In this paper, we investigated how middle and high school students ($N = 512$) construct a scientific argument based on evidence from computational models with which they simulated climate change. We designed scientific argumentation tasks with three increasingly complex dynamic climate models. Each scientific argumentation task consisted of four parts: multiple-choice claim, openended explanation, five-point Likert scale uncertainty rating, and open-ended uncertainty rationale. We coded 1,294 scientific arguments in terms of a claim's consistency with current scientific consensus, whether explanations were model based or knowledge based and categorized the sources of uncertainty (personal vs. scientific). We used chi-square and ANOVA tests to identify significant patterns. Results indicate that (1) a majority of students incorporated models as evidence to support their claims, (2) most students used model output results shown on graphs to confirm their claim rather than to explain simulated molecular processes, (3) students' dependence on model results and their uncertainty rating diminished as the dynamic climate models became more and more complex, (4) some students' misconceptions interfered with observing and interpreting model results or simulated processes, and (5) students' uncertainty sources reflected more frequently on their assessment of personal knowledge or abilities related to the tasks than on their critical examination of scientific evidence resulting from models. These findings have implications for teaching and research related to the integration of scientific argumentation and modeling practices to address complex Earth systems.

Keywords Argumentation · Computational modeling, Earth systems, climate change · Online learning · Instructional technology

Introduction

Climate scientists use computer-based models to make climate predictions. Climate models incorporate the physics and chemistry of the atmosphere and oceans and are used to answer questions such as "what might happen if greenhouse gas concentrations increase?" One of the challenges scientists face in building and using climate models is that they must make a large number of assumptions that simplify complex phenomena in the real world. As a result, every climate model has its own sensitivity—subject to the uncertainties that are inherent in building models of such a complex system (Kerr 2005). Further, the models perform huge numbers of calculations in a much shorter time frame than the time in which the phenomena occur (World Meteorological Organization 2013) and are built to look at trends—changes over time—rather than predicting individual events exactly. Though climate models have improved over time as scientists gain a better understanding of each of the factors and its interactions, uncertainties still remain. Thus, scientists mention sources of uncertainty in their models as part of their construction of arguments to facilitate meaningful

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communications. Despite an overwhelming amount of scientific evidence on causes of climate change described by the Intergovernmental Panel on Climate Change (IPCC) and others working in the field, skeptics tend to focus on where uncertainties remain (Zehr 2000). The predominant form of public discourse on uncertainty in science does not portray uncertainty as an epistemic necessity. Rather, when it comes to climate change, skeptics tend to suggest that scientists do not know *anything* about a topic because they do not know *everything,* or they assert that since nothing is certain, the findings are dismissible (COIN & PIRC 2010). One of the most important tasks in science education then is to help students use and generate evidence related to climate change from models in their academic discourse to learn how to address and communicate uncertainties involved in climate science modeling.

In investigating students' ideas and understanding about uncertainty related to models and modeling, we implemented a set of written scientific argumentations that accompanied students' experimentations with dynamic computational climate models during an online curriculum module. Dynamic computational climate models run on mathematical algorithms and give learners a way to experiment with and visualize interactions and changes in the climate system being modeled (hereafter referred to as "dynamic climate models"). In this paper, we investigate two research questions: (1) How do secondary students incorporate evidence generated from dynamic climate models and uncertainty regarding the evidence into the scientific argumentation tasks?; and (2) how do students' uncertainty-infused scientific arguments change as climate models involve an increasing number of climate factors? The scientific argumentation tasks are part of an online curriculum that uses dynamic climate models to explore factors influencing Earth's atmospheric temperature changes. The curriculum module utilized dynamic climate models and real-world data collected by scientists for students to make claims about questions related to climate, generate evidence from the models and interpret scientists' real-world data to support their claims, and evaluate and elaborate the uncertainty of the claims and evidence. This paper focuses on three scientific argumentation tasks where students use dynamic climate models as a major source of evidence.

Literature Review

Models as Evidence

Scientific models can be presented in a variety of ways including physical artifacts, conceptual diagrams, mathematical expressions, computational algorithms, simulations, and symbolic representations. Regardless of their form, scientific models provide insights into how scientists construct knowledge. A model must be able to explain as many characteristics and phenomena as possible, but also be as simple as possible. Since natural phenomena like climate change are inherently too large and complex to understand completely, "defining the system under study—specifying its boundaries and making explicit a model of that system—provides tools for understanding and testing ideas that are applicable" (NRC 1996, p. 116). The *Framework for K-12 Science Education* (hereafter referred to as the *Framework*, NRC, 2012a, b) endorses using models to understand and predict system's behavior under the systems and system modeling crosscutting concept. Models can enable learners to explore phenomena that are difficult to observe directly (Linn and Eylon 2011) in the real world, and the experience of interacting with them provides understanding that is difficult to achieve without such representations (Ainsworth 2008).

In pedagogical contexts, the term modeling represents various ways in which students can be engaged with their models. Schwartz et al. (2009) identified a set of modeling practices consisting of constructing, using, evaluating, and revising models. For the purposes of this paper, we will focus on ways in which students use and evaluate dynamic climate models to formulate a scientific argument based on evidence from the models.

In particular, computational models have a distinctive benefit in helping students learn about complicated systems. Computational models are run on mathematical algorithms where students select values for a set of manipulative variables that define a system. Sometimes, these complex mathematical calculations can be represented in visual interfaces such as bouncing molecules or in graphical interfaces such as temperature plots. When computational models are a focus of classroom instruction and students are given control, allowing students to systematically modify variables, isolate effects, and draw conclusions, students are able to construct their knowledge of the content and this can lead to more effective learning (Ainsworth and Van Labeke 2004; Gerjets et al. 2010; Pallant and Tinker 2004). Simulations based on computational models cultivate critical thinking by allowing students to examine the behavior of complex systems that are difficult to understand by other means (Feurtzeig and Roberts 1999; Horwitz and White 1988; Levy 2013) and give learners new ways of visualizing complex domains (Ainsworth and Van Labeke 2004; Gerjets et al. 2010). In such cases, simulations based on dynamic computational models have been shown to help students develop both phenomenological and model-based conceptual evidence (Goldberg 2000).

Educational research has shown that powerful online computational models and visualizations can make scientific phenomena accessible and improve understanding (Hegarty 2005; Moreno and Valdez 2005; Tversky et al. 2002). Other research has demonstrated that in certain cases, these visualizations can overload users (Linn et al. 2010). Scaffolds, however, can successfully support the student learning from models (Moreno and Mayer 2007; Xie and Tinker 2006), suggesting that effective use of models depends on appropriate supports within the learning environment. However, few have studied how students use evidence generated from the models in scientific argument construction. In particular, given the fact that models are not exact replicas of scientific phenomena, understanding complex systems such as Earth's climate requires users to acknowledge, "all models are wrong and humility about the limitations of our knowledge. Such humility is essential in creating an environment in which we can learn about the complex systems in which we are embedded and work effectively to create the world we truly desire" (Sterman 2002, p. 501). Thus, coupling modeling with scientific argumentation provides an ideal research context to study how students handle the topic of uncertainty inherent in models.

Argumentation in Science Education

Developing students' abilities to engage in scientific argumentation practice has become an important focus of teaching and learning (Duschl et al. 2007) and has been incorporated into educational reform, making argumentation a key science practice in the Next Generation Science Standards (NGSS) (NGSS Lead States 2013). This comes from nearly a decade of science education research that has shown that making and defending claims with supporting evidence are hallmarks of developing sound scientific understanding (Berland and McNeill 2010; Kuhn 2010; National Research Council (NRC) 2012a; Osborne 2010). Scientific argumentation involves both scientific reasoning to draw inferences from initially available information (Holyoak and Morrison 2005) and critical thinking to sort out evidence for making conditional claims (Yeh 2001). A key goal for science education is to help students seek evidence and reasons for the ideas or knowledge claims that are drawn in science (Driver et al. 2000). Students need opportunities from their earliest science education to construct explanations, and as students' knowledge develops, they should then begin to identify and isolate variables and incorporate observations in their explanations (NRC 2012a). A scientific argumentation framework includes claims (a conclusion about a problem), evidence (data that support the claim), and reasoning (a justification for why evidence supports the claim) (McNeill and Krajcik 2007; McNeill et al. 2006). This argumentation framework can be used as an instructional model as well as an assessment tool.

In his review of literature, Cavagnetto (2010) identified various types of scientific argument interventions to foster scientific literacy involving "learning of argument through immersion, teaching the structure of argument, and emphasizing the interaction of science and society" (p. 336). Most science education research on construction of scientific arguments in written forms has focused on scientific reasoning necessary to coordinate evidence with scientific knowledge. However, the critical reasoning that embodies uncertainties—expressed to reflect argument strength—has been largely neglected in scientific argumentation (Duschl and Osborne 2002; NRC 2012a, b). Therefore, helping students evaluate sources of uncertainty in their claims, and evidence is important for developing scientific argumentation practice. Scientific uncertainty is related to conceptual and methodological limitations imposed by the particular scientific inquiry method applied to an investigation (Allchin 2012). As such, helping students understand the limitations of data and the models from which they are drawing conclusions as well as exploring their own personal uncertainties are key skills that should be incorporated into developing scientific argumentation practices. In our prior studies, we developed a four-part scientific argumentation item format consisting of claim, explanation, uncertainty rating, and uncertainty rationale (Lee et al. 2014). In that research effort, we discovered that students' uncertainty in their argumentation formulation showed dual characteristics involving: personal efficacy with the knowledge, the data interpretation, and the scientific argumentation task as compared to elaboration of scientific sources of uncertainty. We found that a transition occurred in scientific uncertainty rationale from personal accounts to scientific uncertainty sources as their scientific argumentation abilities increased (Lee et al. 2014). As an extension, this study addresses students' construction of scientific argumentation with evidence from simulations based on dynamic climate models and their elaboration of sources of uncertainty.

Climate Science and Learning

Understanding climate as a system means understanding how components of the system interact and influence the climate system behaviors (Pallant et al. 2012) in terms of flow of energy and matter. When exploring climate change, science students also need to understand both natural and man-made causes that can result in climate change and compare scientific data to recognize that the current rapid warming trend is mostly due to man-made causes (NRC 2012b). To help develop this understanding, students should be able to use computational models to predict how modifications to various elements of the Earth's climate system can impact its future climate (NRC 2012a).

Learning about climate change is fraught with misconceptions and incomplete understanding of some complex interactions. Students misunderstand that global climate change (also known as global warming) is due to variations in air pollution (Andersson and Wallin 2000; Boyes and Stanisstreet 1997), ozone layer (Boyes and Stanisstreet 1993, 1997; Fisher 1998;), and solar radiation associated with the Earth's revolution around the Sun (Andersson and Wallin 2000; Koulaidis and Christidou 1999; Boyes and Stanisstreet 1993, 1997, 4). One of the most important causes for the current climate change trend is the greenhouse effect but students have difficulty identifying different types of greenhouse gases (Boyes and Stanisstreet 1993; Fisher 1998) and elaborating how they affect global temperatures. Often, students think greenhouse gases create a layer in the atmosphere (like ozone layer) to trap the Sun's energy (Andersson and Wallin 2000; Koulaidis and Christidou 1999) instead of absorbing the radiation energy emitted by the Earth. Some students think greenhouse gases create ozone depletion, allowing more sunlight to reach the Earth and causing global warming (Koulaidis and Christidou 1999; Boyes and Stanisstreet 1993, 1997). Few students distinguish global warming trends from weather variations. Neither do they recognize links between global warming patterns and increased intensity and frequency of weather events. The flow of elements such as carbon and nitrogen in the climate system is poorly understood because it involves multiple agents in the system (Mohan et al. 2009). Though students consider rising sea levels as an effect of global warming, a great number of students also view ozone layer depletion as an effect of global warming.

It is difficult to understand how the Earth's climate system works and how scientific investigations have discovered complex interactions among diverse elements of the system. Difficulties arise because (1) research about climate change continues and therefore naturally includes uncertainty in claims, theories, evidence, and predictions; (2) climate science needs to be understood as a complex interplay among solar radiation and components of the hydrosphere, geosphere, atmosphere, and biosphere; (3) climate phenomena occur over spatial and temporal scales much larger than students experience day to day; and (4) media reports of climate science are contradictory and sometimes misinterpreted to support political and economical positions. As a result, secondary school students' understandings of current climate science and practices are fragmented, simplistic, and full of misconceptions, misinformation rooted in personal opinions and media influences, and misinterpretation of available scientific data. In this study, we investigate an instructional context where students are provided opportunities to experiment with various climate factors with dynamic climate models. We focus on students' abilities to use evidence from models in their argumentation coupled with their abilities to critically interpret that evidence and recognize limitations of the models they manipulate.

Learning Context

The High-Adventure Science (HAS) project (http://concord.org/HAS) has developed several online weeklong curriculum modules for middle and high school students. These modules address science questions communities of scientists are actively pursuing such as "What will Earth's climate be in the future?", "Will there be enough fresh water?", and "Is there life in space?" In these modules, students use dynamic climate models, analyze real-world data, and engage in scientific argumentation tasks to develop scientific reasoning and critical thinking while learning about science embedded in current scientists' research topics. Since frontier science topics are constantly changing and developing, they provide pedagogically ripe contexts for students to consider uncertainty sources associated with scientific argumentation (Buck et al. in press).

The Climate Module: What will Earth's Climate be in the Future?

In this paper, we focus on one High-Adventure Science module—called "What will Earth's climate be in the future?"—that has students explore past climate changes and learn how mechanisms of positive and negative feedback can affect global temperature. Hereafter, we will refer to this module as the climate module. The climate module includes dynamic climate models, real-world data related to Earth's climate, and a video of a climate scientist describing progress and methods involved in studying Earth's changing climate. The students think about how scientists use models and evidence from the field to make climate change predictions. This module emphasizes student learning about NGSS core disciplinary ideas—ESS2D: Weather and Climate and ESS3D: Global Climate Change—and pays special attention to helping students think about the evidence and how to evaluate the conclusions scientists are able to draw from the evidence.

Table 1 lists five activities in the climate module. Each activity, designed to fit one typical class period of 45 min, consists of several steps, each appearing on a single web page. In Activity 1, students begin by exploring climate data released by the National Aeronautics and Space Administration (NASA) and the Vostok ice cores to investigate temperature trends over different time scales. Students review global atmospheric temperature data and are asked to make predictions about how they think

Table 1 Climate module activity sequence, computational models used and embedded argumentation tasks

Activity sequences	Simulation model use	Argumentation	
		Model based	Data based
1. *Earth's changing climates*			
1.1 What will be Earth's climate in the future?			
1.2 Trends of the past (part 1)			
1.3 Trends of the past (part 2)			
1.4 Predicting the future			ARG 1
1.5 Way, way back in time			
1.6 Vostok research station, Antarctica			
1.7 Predicting the future from the past			
1.8 Looking to the future			
2. *Interactions within the atmosphere*			
2.1 Solar radiation	Model 1		
2.2 Carbon dioxide in the atmosphere	Model 2*	ARG 2*	
2.3 Radiation–gas interactions			
2.4. Earth systems and greenhouse gases	Model 1		
2.5 Atmospheric carbon dioxide levels over time			
2.6 Historical carbon dioxide levels			ARG 3
3. *Sources, sinks, and feedbacks*			
3.1 Carbon cycling in the Earth system			
3.2 Carbon dioxide: solubility in the ocean			
3.3 Changing ocean temperature	Model 3	ARG 4	
3.4 Water vapor: a powerful greenhouse gas	Model 4*	ARG 5*	
3.5 Combining the effects of carbon dioxide and water vapor	Model 5*	ARG 6*	
3.6 Multiple factors			
4. *Feedbacks of ice and clouds*			
4.1 Ice on Earth's surface	Model 6		
4.2 Clouds	Model 7		
4.3 Melting glaciers			
4.4 Arctic sea ice			ARG 7
4.5 Feedback: positive or negative?			
4.6 Clouds: cooling or warming?			
5. *Using models to make predictions*			
5.1 Complex climate models			
5.2 Time lags in temperature changes			
5.3 Meet a climate scientist: Mark Chandler			
5.4 Societal effects			
5.5 Millions of years of data			
5.6 How much reduction?	Model 5	ARG 8	

temperature will change over time. In Activities 2 and 3, students experiment with dynamic climate models to learn about (1) how radiation interacts with Earth's surface and atmosphere; (2) the relationship between ocean surface temperature and carbon dioxide sequestration; (3) the relationship between atmospheric carbon dioxide levels and the amount of water vapor; and (4) the relationship between all three (carbon dioxide, ocean surface temperature, and water vapor). Students consider how evidence derived from experimenting with the models supports their scientific claims and consider sources of uncertainty related to their explanations. In Activity 4, models help students explore how the amount of ice and cloud cover provides negative and positive feedbacks to the climate system under study. In Activity 5, students watch a video of a climate scientist discussing how mathematical climate models reproduce past climates and are used to make predictions about future climate change. The scientist shares the inherent uncertainties with the models while simultaneously showing how the evidence allows scientists to predict climate change with confidence. Finally, students use models to see how all the variables interact with each other to produce global temperature effects. Students consider how changes in human emissions might change average global temperature, and then explain what factors influence their certainty with the conclusions.

The Climate Models

The models used in the climate module are computation-intensive models with visualizations. Computational models are ideal for exploring Earth and environmental science and human impact. Our models simulate the evolution of a system and are based on mathematical algorithms that approximate fundamental physical laws (Pallant and Tinker 2004). Much as scientists do, students can experiment with models by controlling the parameters, starting conditions, and conditions during a run. The models have vivid graphics and run quickly, so that students can experiment and gain insights about the system by carefully observing the evolution of the system. Students can learn both the content and the process of science by experimenting with the models and can see the causes and effects related to different factors interacting in a system because the behavior of these models emerge from scientific rules. They can make predictions and over many runs, evaluate their probabilities, thereby exploring issues of uncertainty inherent in predicting the future.

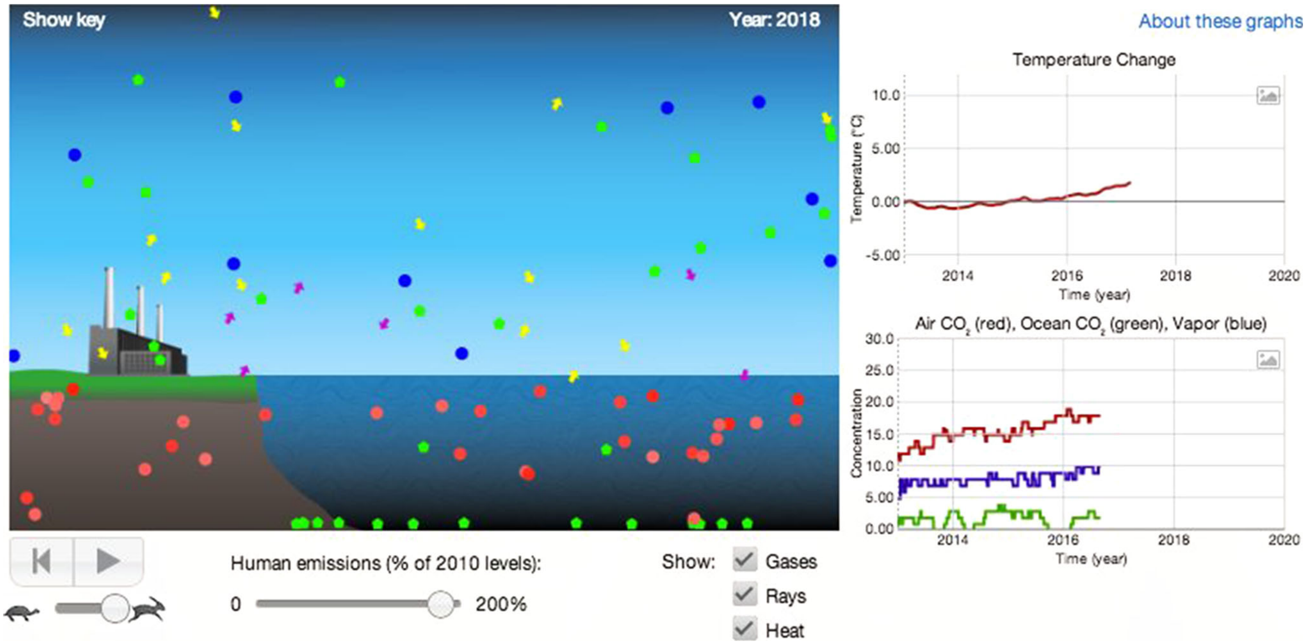
The dynamic climate models are designed to become increasingly more complex as students work through the module. Reflecting this increasing complexity, we used seven different variations of the climate model. See Table 1. The model variations have the same simulation window where solar and infrared radiations interact with various features of the Earth's system. Among the seven variations, all but Model 1 displayed CO_2 and temperature graphs. In Models 2–7, different types of control buttons enabled students to adjust CO_2, ocean temperature, clouds, ice cover, and human emissions. In this paper, we focus on Models 2, 4, and 5, which are associated with three scientific argumentation tasks we analyzed. These three models and argumentation tasks were chosen because they illustrate increasing complexity in the way the model represents climate mechanisms.

In Model 2, students develop an understanding of the relationship between carbon dioxide in the atmosphere and atmospheric temperature (Fig. 1). In this early dynamic climate model, students explore the interaction between incoming solar radiation (yellow arrows) and outgoing infrared radiation (purple arrows) with the carbon dioxide (green dots) in the atmosphere. Students explore, for example, the incoming solar radiation converting to heat when interacting with Earth's surface and observe the IR radiation being absorbed and emitted by CO_2 in the atmosphere. In addition, students see a direct correlation between an increase or decrease in CO_2 (students can change concentration of greenhouse gases in the atmosphere) with temperature by observing plots on graphs near the model. The initial simplified model (Model 2) only takes into consideration one type of greenhouse gas (CO_2) while Model 4 includes water vapor as another greenhouse gas. With Model 5, students learn how feedback can enhance or buffer changes in a system. Positive feedback amplifies changes, and negative feedback tends to dampen changes. When students add more carbon dioxide, for example, Earth's temperature increases; as temperature increases, the model shows an increase in water vapor; as water vapor increases, temperature increases, amplifying the temperature change. Also note that as model variations include new factors in the climate system representation, the underlying computations that produce temperature and CO_2 levels also get complicated. For example, the climate sensitivity increases, resulting in much faster temperature changes in Model 5 when CO_2 water vapor, and atmospheric temperature change more rapidly as a response to changing ocean temperatures as compared to Model 2 when only CO_2 is considered. As the curriculum progresses, the models include additional variables; students can change ice cover, albedo of land surface, ocean temperature, clouds, and human emissions of CO_2. Each additional variable is visually represented in the model, moving parts interact, and output graphs display the results of changing variables. The model and graphs together represent evidence of the system evolving as changes are made.

Three Model-based Argumentation Tasks

We adapted Toulmin's argument structure (1958) to design scientific argumentation tasks. According to Toulmin, an argument consists of six *structural* elements:

- Claim is the conclusion "whose merits we are seeking to establish" (p. 97).
- Data are "the facts we appeal to as a foundation for the claim" (p. 97).
- Warrants "show that, taking these data as a starting point, the step to the original claim or conclusion is an appropriate and legitimate one" (p. 98).
- Backing shows "assurances without which the warrants themselves would possess neither authority nor currency" (p. 103).



(CO_2 task)
What happens if you remove all of the carbon dioxide from the atmosphere?

[Claim] The temperature

- decreases
- increases
- stays the same

[Explanation] Explain your answer

[Uncertainty rating] How certain are you about your claim based on your explanation?

- (1) Not certain at all
- (2)
- (3)
- (4)
- (5) Very certain

[Uncertainty rationale] Explain what influenced your uncertainty rating.

Fig. 1 A dynamic climate model. The *yellow arrows* carry a unit of energy, which is converted into heat in the Earth and ocean, which then can be converted into a unit of IR radiation, represented by *purple arrows*. These interact with the CO_2, represented by *green dots* and water vapor represented by *blue dots*. CO_2 is added into the environment by the slider, which changes human emissions relative to the 2010 levels of emissions (Color figure online)

- Modal qualifiers indicate "the strength conferred by the warrant" (p. 101) and "some warrants authorize us to accept a claim unequivocally with the adverb "necessarily" and others authorize us to make the step from data to conclusion either tentatively, or else subject to conditions, exceptions, or qualifications—in these cases, other model qualifiers such as "probably" and "presumably" are in place" (pp. 100–101).
- Conditions of rebuttal indicate "circumstances in which the general authority of the warrant would have to be set aside … exceptional conditions which might be capable of defeating or rebutting the warranted conclusion" (p. 101) and are directly connected to the choice of the modal qualifier.

We grouped these six elements into four to elicit student responses: (1) a scientific claim for students to ground their argument; (2) an explanation that involves students' citation of data generated from the models they manipulated, warrants connecting data to their claims, and backing on which their warrants are based; (3) a modal qualifier that has students rating the uncertainty of the claim and evidence. We chose uncertainty as a main qualifier in students' argument related to climate change because all science endeavors involve uncertainty sources in them to different degrees depending upon the strength and stability of current knowledge or theory, the robustness and sensitivity of the equipment, and the validity of the scientific inquiry methodology applied to an investigation; and (4) the conditions of rebuttal that include sources of uncertainty. As a result, our structured written scientific argumentation tasks involve: claim, explanation, uncertainty rating, and uncertainty rationale. We used a multiple-choice format for claims, an open-ended format for explanations, a five-point Likert scale uncertainty rating, and open-ended format for the uncertainty rationale. Figure 1 shows how a scientific argumentation task was created following a climate model. Below, we explain each of the three scientific argumentation tasks analyzed in this research. These argumentation tasks correspond to argumentation tasks 2, 5, and 6 in order of appearance in the climate module.

CO_2 Task

In the first task, students explore the interaction between solar radiation and infrared radiation with CO_2. Carbon dioxide is a primary greenhouse gas in the atmosphere. A greenhouse gas absorbs and emits infrared radiation while it does not interact much with incoming solar radiation. This process is the fundamental cause of global warming. Students are able to change the concentration of CO_2 in the atmosphere, follow individual components of the model, and observe the interactions of gases with radiation. Students can observe the graph to see how atmospheric temperature changes as a result of changes they make to CO_2 concentrations. Student use the model to predict what would happen to temperature if carbon dioxide was removed from the atmosphere (Fig. 1).

Water Vapor Task

The second task asks students to use the model to investigate the relationship between atmospheric temperature and water vapor in the atmosphere. Understanding the effects of water vapor as a greenhouse gas is more complex than CO_2. The contribution of each greenhouse gas is affected by the characteristics of the gas and its abundance. The amount of water vapor in the atmosphere exists in direct relation to the temperature. If the temperature increases, more water evaporates from oceans. More water vapor in the atmosphere means higher temperatures. The model shows only water vapor in the atmosphere and liquid water in the ocean. Students use a temperature controller to change the temperature of the ocean. Output graphs show temperature change and water vapor levels over time.

Positive Feedback Task

The third task then combines these variables—CO_2 and water vapor in the atmosphere—and model's positive feedback, i.e., enhanced greenhouse effect. In other words, when CO_2 increases temperature, the water vapor will cause the temperature to increase even more. In this model, students adjust only human emissions of CO_2. The model shows both water vapor and CO_2. Students can analyze the graphs for changes in CO_2 and water vapor levels in the atmosphere as well as changes in air temperature and ocean temperature. As a result of the positive feedback, temperature responds more quickly to changes in CO_2 in this task than in task 1 when CO_2 was the only greenhouse gas.

Methods

Subjects

During the 2011–2012 school year, nine teachers from two middle schools and six high schools implemented the climate module. These schools were located in six states across the USA and represented an equal mix of urban and suburban settings. The teachers taught the climate module to a total of 512 students as part of Earth science, environmental science, geoscience, or exploratory science courses. During the summer prior to the school year, all nine teachers participated in an in-person two-day professional development workshop offered by the project team who designed the module. The teachers were introduced to the dynamic climate models, uncertainty, and scientific argumentation and how the module was designed. The teachers discussed goals, answered the scientific argumentation item sets in context, and reflected on the instructional values and teaching strategies associated with the scientific argumentation prompt sets. All teachers implemented the modules on their own without the project personnel's involvement in terms of teaching and technical assistance. Students worked in small groups during the climate module. The number of students per teacher varied from 10 to 120. Among the students, 50 % were male; 27 % were in middle school; 91 % spoke English as their first language; 24 % received free or reduced lunch; and 49 % used computers for homework regularly. The mean age of the students was 14.3 years (SD = 1.9), ranging from 10 to 19 years. These demographic data indicate that students were sampled to represent a broad spectrum of student populations.

Data Collection

The climate module included 81 prompts that elicited students' responses in various forms such as (1) selecting an answer from multiple choices, (2) writing descriptions or explanations, (3) taking snapshots of the models, and (4) drawing their predictions on a graph. Each scientific argumentation task included four prompts related to claim, explanation, uncertainty rating, and uncertainty rationale.

Table 2 Coding method for explanations

Categories	Criteria	Examples in the CO_2 task
Irrelevant	Did not establish a scientific basis in support of claims	• Blank • I do not know responses • Off-task responses unrelated to climate change topics
Model-based	Incorporated ideas that were illustrated into the climate models	
Output	Output of the model through graphs	• I put a ton of CO_2 in the air and once I started to remove it the temperature decreased • If an increase in carbon dioxide results in an increase in temperature, then a decrease in carbon dioxide would result in a decrease in temperature
Process	Simulated mechanisms at the molecular level	• Because the carbon dioxide would absorb the heat and reflect it back to the earth • With no CO_2 in the atmosphere, there will be less energy being held within the atmosphere • The carbon dioxide helps keep the heat. If there was not any left, then the heat would not be able to be in the earth properly
Misinterpretation	Incorrect interpretations of modeled ideas related to output or process	• I say the temperature increases because the temperature stopped when we released the carbon dioxide, so if we remove it, all the temperature would increase [*misinterpretation of temperature results*] • Without CO_2, there is as much heat being generated [*misinterpretation of simulated greenhouse effect*]
Nominal (names only)	Reference to "model," "graph," and "data" names only without specific details	• That is what the data prove • It shows on the graph
Knowledge-based	Explained using climate knowledge that was not explicitly modeled	
Valid	Non-modeled ideas that are scientific and relevant	• As temperature increases, the form of water will reach its state of being a gas, or water vapor. This is reached when the boiling point of water is met and the water vapor rises as a result
Invalid	Non-modeled ideas that are not scientific and relevant	• The temperature decreases because the CO_2 takes out oxygen from the temperature • The CO_2 would not deplete the ozone, and so, the UV rays would not be able to get in and the temperature will decrease because not a lot of heat is getting to Earth's surface

There were eight scientific argumentation tasks in the climate module, resulting in 32 prompts that were related to scientific argumentation tasks. See Table 1. Among the eight scientific argumentation tasks, for this paper, our analysis focused on the three model-based argumentation tasks (highlighted with asterisks in the table) involving 12 prompts completed by 512 middle and high school students. Among them, 494 competed four argumentation prompts in the CO_2 task, 406 did so in the water vapor task, and 394 did in the positive feedback task, resulting in a total of 1,294 completed scientific argumentation response sets; each set consisted of four separate responses to four scientific argumentation prompts.

Coding Scientific Argumentation Tasks

Students' claims were coded as "correct" if they were consistent with scientific consensus and "incorrect" if not. That is, increases in CO_2 and water vapor will result in rising global temperatures. Students' uncertainty rating was scored using the rating numbers they chose between 1 and 5: 1 for "not at all certain" and 5 for "very certain."

In order to characterize students' explanations, we applied three categories: irrelevant, model based, and knowledge based. Irrelevant explanations included blank responses, responses of "I don't know," and other off-task responses not related to the topic of climate change. Model-based explanations used ideas that were explicitly modeled in the dynamic climate model. On the other hand, knowledge based explanations included particular pieces of scientific knowledge that were not modeled. We did not place a particular value on whether model- or knowledge-based explanations were better for students. Rather, our focus was on how students construct an explanation to answer a scientific question where model results can be relevant to incorporate into their explanations.

We use the CO_2 task (Fig. 1) to illustrate our coding categories. We further classified knowledge-based explanations into two sub-categories of scientifically valid and invalid. To account for different patterns among model-based explanations, we identified four sub-categories: model output, process, misinterpretation, and nominal mention of model. From the climate model used in the CO_2 task, students can observe atmospheric CO_2 levels and atmospheric temperatures on graphical outputs as well as how greenhouse gases interact with solar and infrared radiations. Explanations that mainly cited the former were coded as "model output" while those with the latter were coded as "process." For example, the model output explanations focused on the explicit reference to students' manipulation of a variable in the model resulting in an outcome, i.e., "the more CO_2 in the air, the higher the temperature." On the other hand, "process" explanations describe the process involved in how greenhouse gases interacted with radiation, which was shown in the simulation window. The "misinterpretation" category included student explanations based on misinterpretations of model output or simulated processes. The "nominal" category was assigned to student explanations that simply cited "data," "graph," or "model" in their explanations without mentioning detailed model results or processes (Table 2).

The initial coding of student responses to uncertainty rationale prompts resulted in 13 different categories as shown in Table 3. We then simplified them into four umbrella categories. The "no information" category included blank, off-task responses, and restatements of uncertainty ratings. The "personal" category represented (1) students' personal acknowledgment of not understanding the task, e.g., I do not know what the question is asking, (2) assessment of their status of knowledge and ability related to the science topic addressed in the task, e.g., "I am not a scientist, so I don't know," (3) mention of difficulty with data generated from the models, e.g., "I did not know what the data show," and (4) students' reliance on authoritative sources such as textbooks, teachers, religion, or themselves, e.g., "My prior knowledge about this

Table 3 Coding method for uncertainty rationale

Source of uncertainty	Uncertainty source	Description of categories
No	No response	Did not respond to the related uncertainty item but answered the linked claim and explanation items
Information	Simple off-task responses	Wrote "I do not know" or similar answers
		Provided off-task answers
	Restatement	Restated the uncertainty rating
Personal	Question	Did/did not understand the question
	Authority	Mentioned teacher, textbook, and other authoritative sources
	Lack of knowledge/ability	Did not have knowledge or ability needed in the task
	Difficulty with data	Did not make sense of data generated from the model
Nominal	General knowledge	Possessed general knowledge necessary for the task
	General model	Cited general model or model outputs without specific information
Scientific	Specific knowledge	Referred to/elaborated a particular piece of scientific knowledge directly related to the task
	Specific data from model	Referred to a particular piece of evidence provided in the model
	Limitations in current science knowledge	Mentioned that current scientific knowledge or model is limited to address the climate change task
	Limitations in data from model	Recognized the limitation of data provided in the model and suggested a need for additional data
		Mentioned that not all factors are considered

topic.” The “nominal” category was assigned when students described what piece of information from knowledge or models students would need, but did not provide details on that information or when students mentioned “models” or “graphs” by name only. Examples in the nominal category include, “The graph explained it all” and “That’s what happened on the graph.” The nominal category thus represents students’ acceptance of model results without either scientifically detailed acknowledgment or scientific scrutiny. In the “scientific” category, student’s elaborated particular pieces of scientific knowledge directly related to climate change, e.g., “the less carbon dioxide, the cooler the air is” or particular pieces of model results or scientific data, e.g., “The carbon dioxide in the air makes the temperature increase, and I saw it from watching the chart beside the model.” Also included in the “scientific” category were responses related to recognizing limitations of data, current science, or models, e.g., “because I was observing the data there could be human error,” and “water vapor is not the only cause so other factors would change it also.” Two coders independently scored 31 % of the students’ responses (across teachers) to the three argumentation tasks. Inter-rater reliability was calculated based on the percentage of exact matches between the two raters’ scores. Inter-rater reliabilities were 84, 89, and 90 % for the explanations, and 94, 94, and 95 % for the uncertainty rationale related to the CO_2, water vapor, and positive feedback tasks, respectively. One of the two raters finished coding of the rest of the students’ responses.

Data Analysis

Since our coding methods related to claim, explanation, and uncertainty rationale generated categorical responses, we applied nonparametric statistics such as chi-square in identifying significant relationships among them. When we examined for cross-tabulation tables between two variables, there were no cells with less than five. We set the alpha value at the 0.05 level to identify significant relationships. We then explained each identified significant relationship using examples of students’ actual responses. In addition, we applied ANOVA to the uncertainty rating

Table 4 Frequency distributions of students’ responses to three scientific argumentation tasks (%)

	CO_2 ($n = 494$)	Water vapor ($n = 406$)	Positive feedback ($n = 394$)	Total ($n = 1{,}294$)
(a) Claim				
Consistent	71.9	70.4	82.5	74.7
Inconsistent	28.1	29.6	17.5	25.3
(b) Explanation				
Irrelevant	12.8	12.1	16.0	13.5
Model based				
Output	42.5	45.8	49.2	45.6
Process	16.8	6.2	8.9	11.1
Misinterpretation	14.6	14.5	8.6	12.8
Nominal	5.1	2.0	11.4	6.0
Knowledge based				
Valid	3.2	10.8	3.6	5.7
Invalid	5.1	8.6	2.3	5.3
(c) Uncertainty rating				
1 (not at all certain)	6.7	8.4	14.0	9.4
2	9.7	8.4	10.2	9.4
3	28.5	30.3	24.9	28.0
4	25.3	29.6	27.2	27.2
5 (very certain)	29.8	23.4	23.9	26.0
(d) Uncertainty rationale				
No information	32.4	36.7	33.2	34.0
Personal	23.3	23.2	18.3	21.7
Scientific nominal	28.7	25.9	31.7	28.7
Scientific elaborated	15.6	14.3	16.8	15.5

data when we compared uncertainty rating means across claim, explanation, and uncertainty rationale types. If ANOVA results were significant, we used post hoc tests to further identify significantly different group pairings.

Results

Overall Scientific Argumentation Patterns

Table 4 summarizes descriptive statistics resulting from our scientific argumentation coding across three argumentation tasks. Over the three scientific argumentation tasks, 74.7 % of students' claims correctly predicted that the increases in CO_2 and water vapor levels would result in increases in atmospheric temperatures. Among all students' explanations, 75.5 % were model based and 11.0 % were knowledge based. Model-based explanations mostly addressed model outputs related to greenhouse gas levels and temperatures shown in graphs (45.6 %) as compared to the simulated processes (11.1 %). These indicate that a majority of students drew their evidence from the climate model in their explanations.

Several patterns were observed for students (12.8 %) who did not interpret ideas represented by the model correctly. First, some misinterpretations of model outputs or processes were related to the fact that students likely did not vary the greenhouse gas amounts *enough* to observe the changes in temperatures even though the scientific argumentation tasks reminded students to do so. This occurred because the Earth climate system we modeled has system inertia (much like the real world) where a relatively small change in the greenhouse gas amount would not immediately result in temperature change. To observe the change, students needed to either change the greenhouse gas values large enough or wait long enough. In these cases, students typically wrote in explanations that "[w]hen I added or removed CO_2 molecules, as I looked at the graph, there was no change in temperature." Or some students interpreted small temperature fluctuations as "[temperature stays the same as CO_2 is removed] because the carbon dioxide remains constant while the temperature still changes."

Some students' misinterpretations were related to a misunderstanding of the relationship between greenhouse gases and temperature shown in the model. "The carbon dioxide decreases the temperature, so if it were removed, then the global temperature would rise." Other students' misinterpretations were related to misconceptions related to the greenhouse effect: (1) greenhouse gases as a heat source rather than redirecting Earth's infrared radiation, e.g., "Well the temperature will increase because if the carbon dioxide is in the air and the carbon dioxide is hot the temperature will go up because having something hot in the air will make the temperature go up"; (2) connection to the ozone layer, even though the ozone layer was neither shown in the model nor mentioned in the module, e.g., "CO_2 makes a bigger hole in the ozone layer. With a bigger hole, more heat goes into the Earth and less goes out so the temperature rises. With less CO_2, this doesn't get any bigger so more heat escapes" or "The CO_2 would n't deplete the ozone, and so the UV rays would not be able to get in, and the temperature will decrease because not a lot of heat is getting to Earth's surface"; (3) greenhouse gases interacting with sunlight instead of infrared radiation; and (4) various perceived CO_2 behaviors that were not true such as CO_2 is not a greenhouse gas, CO_2 removes oxygen, CO_2 blocks sunlight, and CO_2 is directly related to humidity. It is surprising that although the climate module did not mention ozone as a main greenhouse gas or the ozone layer, some students still voluntarily elicited ideas related to ozone or ozone layer as part of their explanations.

The overall uncertainty rating distribution resembled a step function where relatively low percentages of students chose rating levels 1 and 2 (uncertain) and higher, evenly distributed percentages of students chose ratings from 3 to 5 (with 5 being very certain). One-third of students did not provide any uncertainty rationale. Among the students who responded to the uncertainty rationale prompts, 21.7 % cited personal sources and 28.7 % cited nominal scientific sources such as model, data, graph, or knowledge without details on how these sources influenced their uncertainty rating. Only 15.5 % of the responses elaborated scientific sources. These findings indicate that (1) students were not familiar with writing uncertainty rationales as one-third opted out; (2) uncertainty ratings were based on a mix of scientific uncertainty and students' own evaluation of their knowledge or modeling skills; and (3) a much smaller number of students cited scientific sources. Among the 15.5 % responses that mentioned scientific sources, very few (8 out of 1,294 completed arguments) recognized uncertainty due to limitations of the current understanding of the climate change topic or those of the model. For example, these responses included statements such as unknown factors other than modeled, "there are probably other factors we don't know about influencing CO_2 levels" and "water vapor is not the only cause so other factors would change it also." A student mentioned limitations of the climate model: "The simulation might not be exactly correct, but it is generally right." Another student mentioned that short-term model outcome might not be accurate as shown in this response: "this is a short-term experiment, there could always be anomalies."

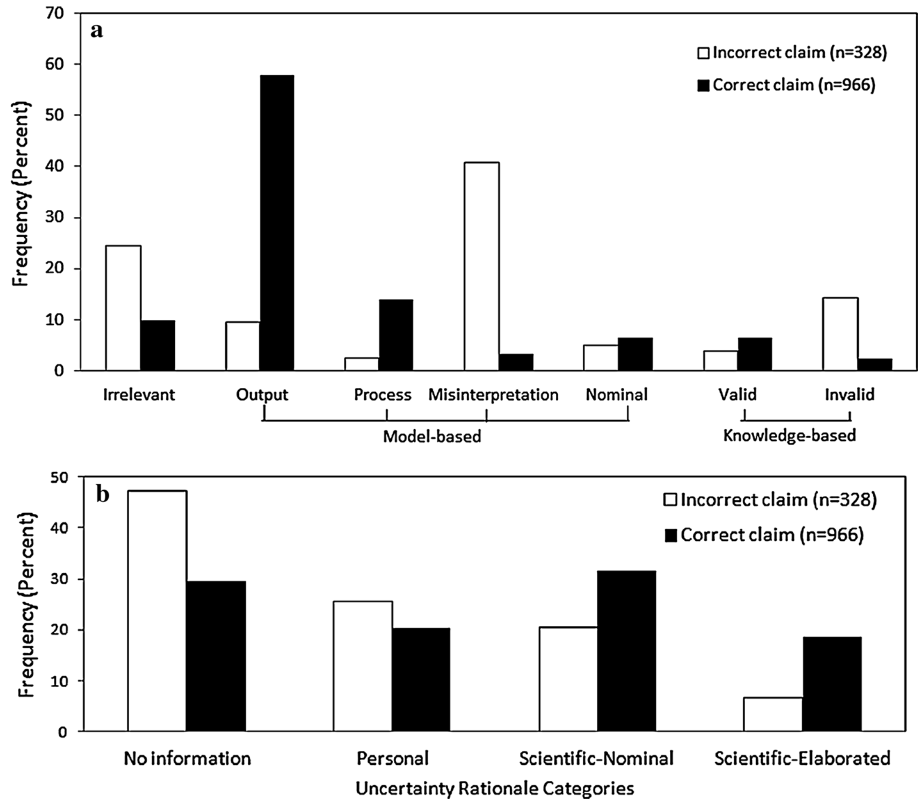


Fig. 2 **a** Distribution of explanations based on the claim students provided. **b** Distribution of uncertainty rationale based on the claim

Table 5 Average uncertainty rating by claim, explanation, and uncertainty rationale

	n	*M*	SD	*t* test/ANOVA results
(a) Claim				
Correct	966	3.63	1.20	$t(1292) = 6.18$, $p < .001$
Incorrect	328	3.15	1.26	
(b) Explanations				
Irrelevant	175	2.51	1.42	$F(6, 1287) = 34.20$, $p < .001$
Model: output	590	3.75	1.08	
Model: process	143	3.99	1.01	
Model: misinterpretation	165	3.21	1.21	
Model: nominal	78	3.45	1.29	
Knowledge: valid	74	3.91	1.00	
Knowledge: invalid	69	3.30	1.06	
(c) Uncertainty rationale				
No information	440	2.88	1.27	$F(3, 1290) = 78.59$, p $< .001$
Personal	281	3.56	1.26	
Scientific nominal	372	3.86	1.00	
Scientific elaborated	201	4.16	0.84	

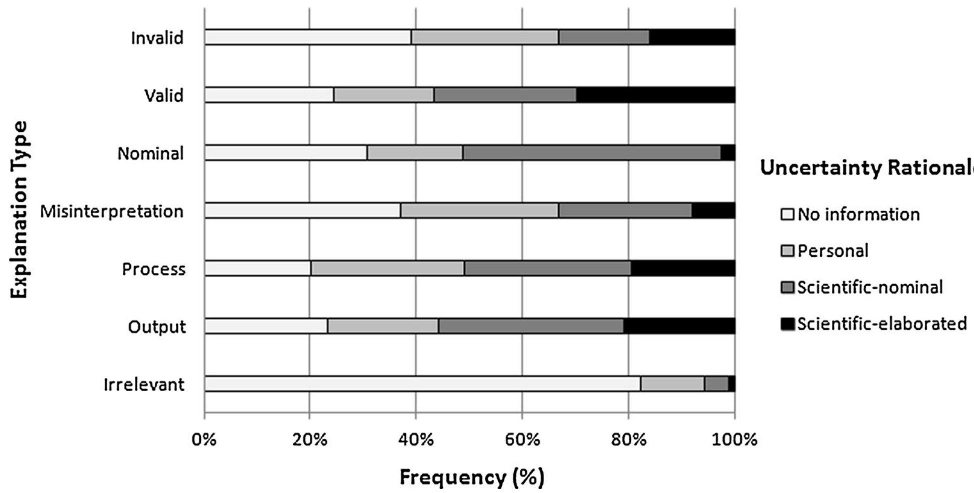
Relationships Among Four Elements of Scientific Argumentation

We examine relationships among the four elements of scientific argumentation in the following way: (1) how explanations, uncertainty rating, and uncertainty rationale relate to making a correct or incorrect claim, (2) how uncertainty ratings correspond to uncertainty rationale and explanations, and (3) how explanations and uncertainty rationale relate.

Making Correct Versus Incorrect Claims

Figure 2a shows the distribution of different types of explanations by claim. Correct claims were mostly based on proper citation of model output results and simulated

Fig. 3 The relationship between uncertainty and explanation type



processes while incorrect claims were mostly based on misinterpretations of models, invalid knowledge, or irrelevant responses. These differences in the distributions of explanation types associated with the correct versus incorrect claims were significantly different, $\chi^2(6, 0.05) = 536.78$, $p < .001$. The mean uncertainty rating of correct claims was significantly higher than that of incorrect claims (Table 5), which indicates that students were more uncertain about their claims when they made incorrect claims. As shown in Fig. 2b, the distribution of uncertainty rationale types related to correct claims was significantly different from that of uncertainty rationale related to incorrect claims, $\chi^2(3, 0.05) = 58.38$, $p < .001$. Correct claims were more closely associated with uncertainty rationale sources related to nominal and elaborated scientific sources while incorrect claims were more closely associated with no information or personal sources of uncertainty.

Uncertainty Rating Differences Across Explanation and Uncertainty Rationale

Table 5 lists average uncertainty ratings associated with claim, explanation type, and uncertainty rationale type. We have already mentioned that students were more certain when they made correct claims than when they made incorrect claims. The average uncertainty rating significantly differed across explanation types. Post hoc tests show that the average rating of irrelevant explanations was lowest (2.51 out of 5) and was significantly lower than any other explanation type ($p < .001$). This indicates that students who could not include any relevant information chose lower uncertainty ratings than those who attempted to explain in climate contexts. Students who used model outputs, processes, and valid scientific knowledge exhibited significantly higher levels of certainty in their arguments than those who misinterpreted models or had invalid knowledge ($p < .001$). When students misinterpreted models or used invalid scientific knowledge, their rating was significantly higher than those who wrote irrelevant explanations ($p < .001$), but significantly lower than those who wrote explanations addressing model results, processes, and valid scientific knowledge ($p < .05$). Explanations based on nominal uses of the model and knowledge were associated with a significantly higher rating than irrelevant responses ($p < .001$), but a significantly lower rating than explanations incorporating model processes ($p < .05$).

The mean uncertainty rating increased as students' uncertainty rationale moved from no information to personal, scientifically nominal, and scientifically elaborated. ANOVA indicated that these means were significantly different, $F(3,1290) = 78.59$, $p < .001$. In addition, Tukey's post hoc tests showed that mean uncertainty ratings were significantly different between all four uncertainty rationale categories at $p < .01$ or lower. Students' rating choices thus appeared to reflect their epistemological stance. When they were familiar or critical with knowledge or evidence, they tended to be more certain than when they were unsure about their knowledge or model results they were observing.

Uncertainty Rationale Versus Explanation

Figure 3 shows a significantly uneven distribution of explanations in each explanation type in terms of uncertainty rationale type, $\chi^2(18, .05) = 287.65$, $p < .001$. A few distribution differences were noteworthy. First, irrelevant explanations were predominantly associated with no information in student uncertainty rationales. Second, students who used model results, processes, and valid scientific knowledge were more likely to identify scientifically elaborated sources of uncertainty. Third, students who nominally mentioned model and knowledge were more likely to identify scientific uncertainty sources nominally rather than elaborate their sources of uncertainty. Fourth, even though students used model results and processes, or valid knowledge, many did not take the opportunity to scientifically elaborate uncertainty sources, indicating that writing uncertainty rationale was not always eliciting the same aspect of cognition.

Scientific Argumentation Patterns Across Tasks with Increasing Complexity

According to the climate module sequence, the CO_2 task occurs with the dynamic climate model that only incorporated the CO_2 levels affecting the global temperature calculation. This argumentation task occurred on the second day of the module. On the third day, students were introduced to the role of the ocean, which can release CO_2 gases into the atmosphere as well as contribute water vapors as another greenhouse gas type. In these models, new factors were incorporated into the temperature calculations. Thus, the impact of CO_2 changes would appear to be greater on the temperature changes than CO_2 alone. The climate module was sequenced in this way for students to interpret the positive feedback involving CO_2 in the atmosphere, CO_2 from the ocean as temperature changes, and water vapor from the ocean in affecting global temperatures. We wanted to examine whether these complex mechanisms were noticed by students. Table 4 lists distributions of claim, explanation, uncertainty rating, and uncertainty rationale across three tasks. We base our results on these distributions in this section.

Claim

According to the chi-square test results, significantly more correct claims were made for the positive feedback task (82.5 %), than those for the CO_2 task (71.9 %), or for the water vapor task (70.4 %), $\chi^2(2, .05) = 18.6$, $p < .001$. This can be explained by the fact that the global temperature responds to CO_2 increases much faster when the model involves the positive feedback loop rather than without, making students notice the positive correlations much easier from the model.

Explanation

Across three tasks, more students were able to successfully incorporate simulated processes in their explanation for the CO_2 task as compared to the other two where more complicated mechanisms were shown in the simulation window. Instead, more and more students relied on model-based graph outputs in their explanation for the most complex task while this also increased nominal uses of the model or knowledge at the expense of more detailed mechanisms or descriptions of model outputs. Students produced more knowledge-based explanations that were not modeled in the water vapor task than the CO_2 and the positive feedback tasks, indicating that more students experienced difficulty understanding the model with the water vapor as a major factor and thus required bringing more knowledge outside of the models to write explanations than the other two tasks. Misinterpretations of the model results or simulated processes decreased by half for the positive feedback task in part because interpreting the model outputs between CO_2 increase and temperature increase was likely much easier to notice than the other two tasks.

Uncertainty Rating

As the complexity of the climate model increased from CO_2 to water vapor to positive feedback tasks, the average uncertainty rating decreased significantly, $F(2,1291) = 4.50$, $p < .01$, meaning the ideas represented in the models became more and more uncertain to students. The mean uncertainty rating of the CO_2 task was highest ($M = 3.62$, SD $= 1.20$) and that of the positive feedback task was lowest ($M = 3.37$, SD $= 1.32$). The mean uncertainty rating of the water vapor task was in the middle ($M = 3.51$, SD $= 1.18$). Tukey's post hoc test indicates that the mean uncertainty rating of the CO_2 task was significantly different from that of the positive feedback task, $p < .01$.

Uncertainty Rationale

No significant differences existed in uncertainty rationale types across three tasks, despite changes in model complexity, $\chi^2(6, 0.05) = .27, p = .62$. This indicates that the uncertainty rationale did not depend on the complexity of the models.

Discussion

In teaching and learning climate science in secondary school classrooms, the use of models has played an important role. Much of current debates on claims about future changes in the climate are based on models that scientists develop and test based on their current understandings of climate science. The models are not an exact replica of the real world but incorporate current conceptualizations and understandings of the real world. As such, uncertainty associated with current conceptualizations and understanding of climate science makes climate science a fertile curriculum context where uncertainty-infused scientific argumentation is meaningful and pedagogically appropriate (Lee et al. 2014). This study examined how secondary school students incorporate evidence generated from dynamic computational climate models in formulating scientific arguments following structured prompts.

Overall, results of this study indicate that most students can incorporate results from their own experimentation with computational models as evidence in their explanations as a majority of students (75.5 %) used model-based results in building their arguments. Even though the dynamic climate model we developed shows how greenhouse gases interact with solar and infrared radiation, students mainly focused on the temperature output in relation to changes in the greenhouse gas level in their explanations. This indicates that students used the model to build a simple causal link between two variables—greenhouse gas concentration and global temperature—rather than to develop an explanatory account about the interactions responsible for global warming.

The design of the dynamic climate model and the representation of the emergent outcome itself did influence the ways in which students incorporated the evidence in their explanations. The climate models were intended to simplify a very complex system. Nonetheless, even the simplest models had many moving parts. Scaffolds within the visualizations, such as following an individual greenhouse gas molecule, as well as the output graphs, were designed to help students recognize interactions with the systems and changes in system outcomes (e.g., global temperatures) over time. The temperature graphs in particular were well recognized by students as changes occurred to the whole system. As the models got more and more complex, it appears that students started paying more attention to the output graphs as they were simpler to interpret than the more complex emergent phenomena represented in the simulation window of the dynamic climate model. As the tasks and representations became more complex, students' reliance on clear, simple, obvious results from their experimentation became more predominant. For example, students were able to recognize positive correlations between CO_2 levels in the atmosphere and temperature changes when the positive feedback mechanisms were working in the background of the dynamic climate model in the positive feedback task, as compared to when the model relied on the direct causal relationship between CO_2 levels and temperature in the CO_2 task. Since the temperature outcome was much more obvious for students to notice on the graphs, students were much more willing to build a simple causality between CO_2 and temperature in the positive feedback task even though the mechanisms, in fact, became much more complex. It is our view that students stopped relying on understanding the complex causal relationships involving feedback in developing their arguments but rather used the more obvious cause and effect as shown in the graphs, and reducing the argument to a more simplistic level.

It is noted that the embedded argumentation tasks in this study required students to make claims, use evidence from the models, rate the certainty of their claims and evidence, and give a rationale for their certainty ratings. Though students have been making claims in science and using evidence from experiments and texts to support their claims, students have had little to no exposure with thinking about sources of uncertainty in general and with models in particular. Students' uncertainty rationales rarely addressed limitations of the models or the uncertainty inherent in making predictions—a key component of thinking about future climate change. More typically, students presented their own lack of scientific understanding and personal skills as their main source of uncertainty. Though understanding uncertainty has been described as a fundamental part of scientific literacy necessary for making sense of science (Deboer, 2000), it has not been adequately addressed in science classrooms. It is noteworthy that more than 34.0 % of students' scientific arguments did not have written uncertainty rationales while only 13.5 % did not have written explanations. This indicates that consideration of uncertainty sources in science learning is even more novel than writing explanations. In our teacher feedback survey, when asked about their teaching of the climate module with uncertainty-infused scientific argumentation tasks, teachers mentioned that "students seemed to struggle in identifying the level of certainty. We talked about this each day after finishing our work. Some of the students are too confident in their answers." Another teacher mentioned that students did not seem to appreciate differences between explanations and uncertainty rationale and "felt as though they were having to explain their thinking twice. They feel like parts of this aspect are somewhat redundant." The High-Adventure Science modules have begun to explicitly bring discourse about uncertainty into argumentation skills; there clearly need to be more scaffolds related to focusing on sources of scientific uncertainty rather than personal levels of uncertainty to help students write scientific rationales.

Although students made progress in understanding factors affecting climate change, it is noted that students' prior conceptions also influenced students' interpretations of outcomes. Research has shown that students' preconceptions significantly influence students' learning about the greenhouse effect and global warming (Reinfried and Tempelmann 2013). Additionally, research has shown that prior knowledge affects how one interprets and understands visual representations of complex phenomena. Studies have shown that visualizations can help students develop better understanding, but in some cases, students retain misconceptions and may even develop new misconceptions (Kelly and Jones 2007; Tasker and Dalton 2008). We found evidence that students who approached the models with misconceptions—in this case related to the flow of energy or ozone—interpreted the models incorrectly based on those misconceptions. This highlights the need to address students' prior knowledge or alternative ideas explicitly when teaching climate science with models.

This study was descriptive in nature and was not conducted to establish a causal claim about how computational models influence students' scientific argumentation abilities. An experimental design with a control group is necessary to build causal claims. We sampled students from various school settings to represent a broad spectrum of student populations in the USA. However, they were not sampled randomly from the entire population. We analyzed students' responses to a selected set of scientific argumentation tasks and did not take into account teacher effects. Further research is necessary about how teachers can shape classroom environments that are or are not conducive to the intended learning of scientific argumentation through computational models.

Conclusion

Scientists use computational models to investigate system dynamics and make claims about future climates. We designed a curriculum module in which students learn climate science through formulating scientific arguments based on computational models. Results of this study indicate that after experimenting with dynamic climate models and observing changes in the simulated climate system, students were able to incorporate evidence from the models and associated graph outputs to develop their scientific arguments about climate change. However, students' use of model evidence resorted to simplistic causality involving one cause matching with one effect and did not extend to complex causality involving feedback loops among three or more climate factors. In the positive feedback case, the tendency to use a simplistic causality is even more pronounced than complex causality, giving students a false sense of confidence because the link between a cause and an effect is amplified. This finding provides a cautionary tale for educators and curriculum designers who select complex models as a way to teach complicated system dynamics. In addition, our study results indicate that students' treatment of uncertainty rationale needs explicit scaffolding from teachers or curriculum materials to engage students in recognizing and properly responding to model limitations.

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